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# The moderating effects of greenspace on the association between neighbourhood disadvantage and obesity among mid-to-older aged Australian adults

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A B S T R A C T

This study examined whether the association between neighbourhood disadvantage and obesity was moderated by quantity and quality of greenspace. The sample included 2848 mid-to-older aged adults residing in 200 neighbourhoods in Brisbane, Australia from the HABITAT study. Self-reported height and weight were used to calculate body mass index (BMI), neighbourhood disadvantage was measured using a census-derived composite index and greenspace was measured geospatially. We found evidence of moderation by park quality: lower average BMI at higher levels of park quality was shown in the Q3 rather than the Q1 (least disadvantaged) neighbourhood disadvantage group. The findings suggest that, for reducing socioeconomic inequalities in obesity, the quality of greenspace is imperative.

## 1. Background

Obesity has become a global public health challenge (World Health Organization, 2021). According to the World Obesity Federation (2023), the global prevalence of the overweight or obese in those aged over 5 years was 2.6 billion in 2020, accounting for approximately 38% of the total population. It is projected that the prevalence of the overweight and obese will rise to 3 billion in 2025, accounting for 42% of the total population. Overweight and obesity are defined as abnormal or excessive fat accumulations that are considered a health risk (World Health Organization, 2021). Overweight and obesity are often measured using the body mass index (BMI), an internationally recognised measure (Centers for Disease Control and Prevention, 2023). BMI classifications of overweight or obese are considered a health risk and are associated with over 30 diseases, including 17 types of cancers, four cardiovascular diseases, three musculoskeletal conditions, type 2 diabetes, dementia, asthma, and chronic kidney disease (Australian Institute for Health and Welfare, 2023). In addition, overweight (including obesity) is the second leading risk factor contributing to ill health and death (after tobacco use), accounting for 8.4% of the total disease burden in Australia in 2018 (Australian Institute for Health and Welfare, 2023). Obesity rates among Australians are sizeable. When comparing the proportion of obese men and women in The Organisation for Economic Cooperation and Development countries, Australia had the fourth highest proportion of obese men (32%), trailing only New Zealand, Hungary, and the United States; and the ninth highest proportion of obese women (29%), out of 21 countries (Australian Institute for Health and Welfare, 2023).

The root causes of overweight and obesity are diverse and complex (Schalkwijk et al., 2018). One factor that has been shown to be significantly associated with overweight and obesity is the socioeconomic conditions in which people live (Anekwe et al., 2020). Characteristics of socioeconomically disadvantaged neighbourhoods, such as a poor built environment for promoting physical activity, insufficient access to food outlets, safety concerns or higher levels of stress may increase the risk of overweight and obesity (Lovasi et al., 2009). For instance, Rachele et al. (2017) demonstrated an association between neighbourhood socioeconomic disadvantage and increased BMI among mid-to-older aged adults, while Rachele et al. (2019) further established that both individual and neighbourhood-level socioeconomic factors significantly influenced BMI, highlighting the multifaceted impact of socioeconomic disadvantage on obesity. These studies underscore the importance of considering both community and individual socioeconomic factors in understanding

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and addressing obesity. Furthermore, Feng and Wilson (2015) examined the socioeconomic trajectories in BMI across the life course. Their longitudinal study of over 21,000 Australians revealed that socioeconomic factors significantly influenced obesity risk. Overall, the existing evidence suggests that neighbourhood-level socioeconomic factors contribute to obesity, and any viable approach to addressing the obesity epidemic must take factors at this level into account. This is further exacerbated by an ageing population and people transitioning into retirement as people are spending more time in their neighbourhoods. In Australian adults, the proportion classified as overweight or obese has been shown to increase with age, peaking in the 65–74 year age group (Australian Institute for Health and Welfare, 2023). Similar trends can be seen globally. A meta-analysis indicated that the prevalence of central obesity in those aged 40 years and over was almost double that of those aged 15–40 years (Wong et al., 2020), though this may be partially due to decreased physical activity in older age groups. Furthermore, Australia has an ageing population (Australian Bureau of Statistics, 2020). To support ageing in place and reduce the prevalence of obesity among older adults it is necessary to understand how greenspace is utilised by this age group.

Several studies have explored the mechanisms underlying the associations between neighbourhood disadvantage and obesity. A recent systematic review by Selvakumaran et al. (2023) examined built environment attributes as potential moderators of the association between neighbourhood disadvantage and overweight/obesity in adults. The systematic review indicated that residents of more disadvantaged neighbourhoods were at an increased risk of obesity, with this trend being more pronounced in inner urban areas, while somewhat less evident in rural settings. The review also examined the role of built environment attributes, such as walkability, street connectivity, and access to physical activity facilities, in moderating this relationship. However, the results regarding these attributes are mixed, with some studies finding moderation effects, while others reported no effect. Despite the inconsistency in findings related to various built environment characteristics, the authors identified greenspace as a potential moderator that is yet to be explored. The review suggests that access to greenspace may play a crucial role in mitigating the effects of neighbourhood disadvantage on obesity.

Emerging evidence suggests a nuanced relationship between greenspace and weight status. A recent systematic review by de la Fuente et al. (2020) examined the relationship between greenspace access and obesity among adults, and found evidence for lower rates of overweight and obesity among those living near greenspace. In a large cross-sectional study, Lee et al. (2015) found significant associations between objectively measured neighbourhood greenspace and reduced risk of obesity and abdominal obesity. Furthermore, a recent study by Blas-Miranda et al. (2022) explored the association between greenspace and obesity in the Mexican mid-to-older aged adult population (20–59 years). They found that higher residential exposure to greenspace was associated with a mean decrease in BMI of $-1.1$ kg/m$^2$, suggesting a protective association between greenspace and obesity among adults. The mechanisms linking greenspace and obesity are clear: greenspace provides a setting for physical activity. In areas with more greenery, adults, especially those in mid-to-older age groups, tend to engage more frequently in activities like walking and moderate-to-vigorous physical exercises. This higher rate of physical activity in greener neighbourhoods suggests a strong correlation between the presence of greenspace and regular participation in health-promoting physical activities (Astell-Burt et al., 2014). A factor influencing the amount of physical activity within parks is the features located within. While access to parks has been shown to be important for physical activity, studies have highlighted the importance of park quality on physical activity. Features and amenities within a park, such as shaded areas, walking and biking paths, well-maintained facilities, and sports courts, are crucial indicators of its quality (Jamalishahni et al., 2023). Furthermore, studies by McCormack et al. (2004) and Wendel-Vos et al. (2004) have demonstrated that effective park management and maintenance are correlated with increased intensity in physical activities. In addition to facilitating physical activity, greenspace may potentially impact BMI through other mechanisms. Greenspace has been shown to alleviate stress, improve mental wellbeing and provide an opportunity for social interaction, which have been linked with lowering the risk of obesity (Luo et al., 2020).

Of note, the benefits of greenspace availability and quality are socioeconomically patterned, with more socioeconomically disadvantaged individuals often experiencing more significant health benefits from access to public greenspaces and parks than their more affluent counterparts (Rigolon et al., 2021). Despite these findings, existing evidence on whether greenspace moderates the association between neighbourhood socioeconomic disadvantage and obesity remains limited. This gap in the literature underscores the need for further research to better understand the role of greenspace in mitigating socioeconomic inequalities in obesity. Given existing area-level socioeconomic inequalities in obesity and the potential for greenspace to reduce these inequalities, an investigation of the moderating effect of greenspace on associations between neighbourhood disadvantage and obesity is warranted. The aim of this study is to examine whether the association between neighbourhood socioeconomic disadvantage and obesity is moderated by quantity and quality of greenspace.

## 2. Methods

### 2.1. Population and data

The study utilised data obtained from the How Areas in Brisbane Influence healTh And acTivity (HABITAT) project (Turrell et al., 2020). The main objective of the HABITAT study is to analyse patterns in physical activity, sedentary behaviour, and health from 2007 to 2016. In addition, the study aims to examine the various impacts of environmental, social, psychological, and socio-demographic factors on these observed changes.

### 2.2. Sample design and neighbourhood-level unit of analysis

Specific details about HABITAT's sampling design have been published elsewhere (Turrell et al., 2020). Briefly, a multi-stage probability sampling design was used to select participants via a stratified random sample from Census Collector's Districts (CCD). In 2006 CCDs were the second smallest geographic area defined in the Australian Standard Geographical Classification (ASGC). CCDs ($n = 1625$) were allocated a score using the Australian Bureau of Statistics (ABS) Index of Relative Socioeconomic Disadvantage (IRSD). The scores were ranked and appointed into deciles. From these deciles 20 CCDs were randomly selected ($n = 200$). CCDs at baseline contained an average of 203 occupied private dwellings, and are embedded within a larger suburb, hence the area corresponding to, and immediately surrounding, a CCD is likely to have meaning and significance for their residents (Turrell et al., 2020).

### 2.3. Data collection and response rates

In May 2007, a mail survey was distributed comprising a structured self-administered questionnaire to a sample of 17,000 potentially eligible participants. After excluding 873 contacts that were not relevant to the study due to reasons such as being deceased, no longer residing at the given address, or being unable to participate due to health-related issues, a total of 11,035 surveys were collected and considered valid. This resulted in a baseline response rate of 68.3%. The response rates of participants who were both in-scope and contactable in the years 2009, 2011, 2013, and 2016 were 72.6% ($n = 7866$), 67.3% ($n = 6900$), 67.1% ($n = 6520$), and 58.7% ($n = 5187$), respectively. The present study utilised data from the fifth wave (2016) of data collection, comprising a sample size of 5187 participants.

### 2.4. Exposure variables

Neighbourhood disadvantage: Substantial changes were made to the standards and geographical classifications from the ASGC to the Australian Statistical Geography Standard (SA1) in 2011 and consequently, there were changes to geographical units and boundaries used for measuring spatial data (Australian Bureau of Statistics, 2024). To account for this, neighbourhood socioeconomic disadvantage was derived using a weighted linear regression, using scores from the ABS' IRSD from each of the previous censuses from 1986 to 2016. The IRSD score is derived from 17 socioeconomic indicators of the residents within the area. This includes the percent of people aged 15 years and over whose highest level of education is Year 11 or lower, unemployed, employed people classified as Labourers, low rent private dwellings, one parent families, people under the age of 70 with disability, divorced/separated, machine operators/drivers, low skill Community and Personal Service workers, occupied dwellings with no car, overcrowded dwellings, those aged 15 years and over who have no educational attainment, people who do not speak English well (Australian Bureau of Statistics, 2018). The derived IRSD scores were then grouped into quintiles, with Q1 representing the 20% least disadvantaged areas relative to the whole of Brisbane and Q5 the most disadvantaged 20%.

Greenspace quantity and quality: The development of the greenspace measures is described in more detail elsewhere (Jamalishahni et al., 2023). Briefly, 1.6 km network buffers around each participants' residence were used to calculate greenspace measures, using park quality and quantity as proxy measures for greenspace. These distances were chosen based on previous research indicating the average distances people, especially older adults, are willing to walk for utilitarian purposes (Garrard, 2013; Sugiyama et al., 2019). Park quantity was measured by compiling the proportion of greenspace within each 1.6 km network buffer. Park quality was measured by first assigning a park score by summing the number of park facilities. Park facilities included features that are suitable for older adults, such as benches and toilets; amenities that foster social interaction, such as picnic tables and areas for dogs to roam freely; and elements that have been shown to improve park usage among the participants of the HABITAT study, including BBQ areas, drinking fountains, sufficient lighting, public toilets, and clear directional signage. Moreover, the inclusion of car parks, bike racks, and dedicated walking and biking paths were considered essential, as these facilities promote diverse modes of transportation, thus enhancing the overall accessibility of the greenspace. The number of park facilities was then divided by the total area of each park. As a buffer may include more than one greenspace, geographical information systems (GIS) was used to attribute the facilities score to the associated greenspaces within a buffer. The park quality score of a buffer was calculated by summing the total greenspaces' facilities scores and then dividing by the total greenspace area. The median (interquartile range) park quality score was 4.68 (0, 122.73).

### 2.5. Outcome variable

Body mass index: Participants were asked "how tall are you without shoes on?" and were able to respond in either centimetres or feet and inches; and "how much do you weigh without your clothes or shoes on?" and were able to respond in either kilograms or stones and pounds. BMI was calculated as weight in kilograms, divided by height in meters squared (Safaei et al., 2021).

### 2.6. Covariates

Neighbourhood self-selection: A lack of adjustment for residential self-selection is problematic for analyses of causal inference between neighbourhood walkability characteristics and obesity, due to the risk of confounding. That is, relocating residents may select their new neighbourhood according to their lifestyle and personal preferences, and those seeking to improve their health (e.g. through increases in physical activity or changes to diet) may seek neighbourhoods that facilitate that objective (McCormack and Shiell, 2011; Van Dyck et al., 2011). To assess residential attitudes, participants were asked to respond on a five-item Likert scale, ranging from 'strongly disagree' to 'strongly agree' on 18 statements regarding "How important were the following reasons for choosing your current address?". Examples of statements included "Affordability of land, housing or rent", "Closeness to open space", and "Closeness to schools". Principal component analysis with varimax rotation at baseline showed that the items loaded onto three factors, subsequently described as 'destinations' (three items, $\alpha = 0.81$) 'nature' (three items, $\alpha = 0.78$) and 'family' (two items, $\alpha = 0.62$). Each of the three factors were entered into models as standardised measures with a mean of 0 and a standard deviation of 1.

Age and Gender: Participants provided self-reported information regarding their date of birth and gender. The mean age for this sample was 61 years (range 48–77 years). For descriptive purposes, the age variable was categorised into five separate groups: 44–49 years, 50–54 years, 55–59 years, 60–64 years, 65–69 years, 70–74 years and 75–79 years. However, age was entered into models as a continuous variable.

Education: Participants were asked to provide details regarding the highest level of education they had achieved. Responses were coded as mutually exclusive categories: (1) bachelor's degree or higher (including postgraduate diploma, master's degree, or doctorate), (2) diploma (associate or undergraduate), (3) vocational (trade or business certificate or apprenticeship), or (4) no qualifications beyond secondary school.

Occupation: Participants who were employed at the time of completing the survey were requested to provide their job title and then to describe the main tasks or duties they performed. This data was then classified according to the Australian Standard Classification of Occupations (ASCO) as outlined by the ABS (Australian Bureau of Statistics, 1997). The initial ASCO classification, consisting of nine levels, was subsequently condensed into four separate categories. These categories are as follows: (1) managers/professionals (managers and administrators, professionals, and paraprofessionals), (2) white-collar employees (clerks, salespersons, and personal service workers), (3) blue-collar employees (tradespersons, plant and machine operators and drivers, and labourers and related workers), (4) not in the Labor force (missing, not employed, home duties, students, retired, permanently unable to work or other).

Household income: Participants in the study were given instructions to provide an estimation of the overall annual household income before taxes. This estimation was obtained through a single question that included 13 categorical response options. In order to conduct an analysis, the data was re-coded into six different categories: (1) $\geq$ AU $130,000, (2) AU$129,999–72,800, (3) AU$72,799–52,000, (4) AU $51,999–26,000, (5) $\leq$ AU$25,999, or (6) Not classified (i.e., left the income question blank, ticked 'Don't know' or 'Don't want to answer this').

### 2.7. Statistical analysis

Wave 5 of HABITAT (2016) was selected as it is the most recent. Furthermore, it was posited that the effect of greenspace would play out over a number of years, and so only participants who remained at their original residence since baseline (2007) were included leaving n = 3597 in-scope participants. We chose to only include those who remained as their original residence as they had a consistent level of neighbourhood disadvantage and exposure to greenspace (Braun et al., 2016). After excluding participants who had missing data on occupation (n = 435), household income (n = 76), neighbourhood self-selection (n = 139) and BMI (n = 99), the final analytic sample was n = 2,848, 79% of in-scope participants. Across the 200 neighbourhoods included in our study, the mean number of participants per group was 14.24, with a standard deviation of 8.88. Although our sample size has decreased, when compared to the HABITAT cohort wave 5, HABITAT cohort at baseline, and Brisbane population aged 40–65 years, the proportions of each sociodemographic characteristic in our sample size have not meaningfully changed. Sensitivity analysis revealed that missing participant data was associated with demographic factors but not with our outcome variable – BMI. As the missing is related to covariates and not the outcome variable, it is termed missing at random. Model estimations remain unbiased as long as dropout-related covariates are integrated into the models and there are no further unmeasured covariates associated with dropout (Fitzmaurice et al., 2011). The final analytic sample is presented in Table 1.

A multilevel modelling approach was undertaken as it considers that individuals are nested (clustered) within neighbourhoods (University of Bristol, 2023). Multilevel linear regression models, with a random effect specified at the neighbourhood level, were undertaken in two steps. First, the association between neighbourhood socioeconomic disadvantage and BMI is presented with each of the park variables (i.e., quantity and quality) to form the base model (Model 1) for effect measure modification. Second, to examine effect measure modification, an interaction term between neighbourhood disadvantage and each park variable, quantity (Model 2) and quality (Model 3), was added. The analytic approach to effect measure modification followed the principles outlined in previous epidemiological literature (Knol and VanderWeele, 2012). Likelihood ratio tests, as well as examination of individual coefficients, was used to assess moderation in nested models. Potential confounders age, sex, socioeconomic indicators (e.g., education, occupation, household income), and residential self-selection were included in all models. All analysis was undertaken using Stata SE version 16 (StataCorp, 2019).

**Table 1**
Descriptive statistics for each of the sociodemographic characteristics and BMI for the analytic sample: HABITAT Wave 5, 2016.

| *Total* | n = 2848 | BMI |
|---|---|---|
| | % | Mean (SD) |
| ***Neighbourhood disadvantage*** | | |
| Q1 (least disadvantaged) | 29.2 | 26.68 (5.30) |
| Q2 | 22.8 | 27.28 (5.10) |
| Q3 | 20.1 | 27.48 (5.59) |
| Q4 | 14.3 | 28.40 (6.55) |
| Q5 (most disadvantaged) | 13.6 | 28.28 (7.02) |
| ***Sex*** | | |
| Males | 42.9 | 27.67 (4.92) |
| Females | 57.1 | 27.27 (6.37) |
| ***Age*** | | |
| 44–49 years | 2.3 | 28.21 (6.11) |
| 50–54 years | 20.8 | 27.63 (5.97) |
| 55–59 years | 22.7 | 27.52 (5.54) |
| 60–64 years | 19.9 | 27.28 (5.29) |
| 65–69 years | 19.1 | 27.38 (6.06) |
| 70+years | 15.3 | 27.23 (6.17) |
| ***Education*** | | |
| Bachelors+ | 33.3 | 28.18 (6.45) |
| Diploma/Associate Degree | 16.8 | 28.03 (5.95) |
| Certificate (trade/Business) | 11.9 | 27.01 (5.17) |
| None beyond school | 37.9 | 26.66 (5.18) |
| ***Occupation*** | | |
| Manager/professional | 30.8 | 27.07 (5.15) |
| White collar | 20.5 | 27.80 (5.81) |
| Blue collar | 10.5 | 27.60 (5.84) |
| Home Duties | 5.1 | 26.97 (5.67) |
| Retired | 24.3 | 27.32 (6.08) |
| Not easily classifiable | 8.8 | 28.34 (6.93) |
| ***Household Income*** | | |
| $130000+ | 21.7 | 27.02 (4.85) |
| $72800-129999 | 24.3 | 27.68 (6.03) |
| $52000-72799 | 12.8 | 27.37 (5.72) |
| $26000-51599 | 18.3 | 27.69 (6.11) |
| Less than $25999 | 11.0 | 27.96 (6.72) |
| Don't know | 2.4 | 27.06 (5.75) |
| Don't want to answer | 9.5 | 26.91 (5.45) |

## 3. Results

Mean BMI was lowest among those living in the least disadvantaged neighbourhoods, those aged over 70 years of age, those with no post-school qualifications and those in home duties. Mean (standard deviation (SD)) park quantity and quality by each quintile of neighbourhood disadvantage are presented in Table 2. Q1 (25.58 (SD 11.35)) and Q5 (17.98 (SD 10.64)) had the highest and lowest park quantity respectively, similarly Q1 (7.18 (SD 8.61)) and Q5 (6.19 (SD 14.25)) had the highest and lowest park quality respectively.

Results of the multilevel linear regression are presented in Table 3. There were significant differences in BMI between neighbourhood socioeconomic disadvantage groups, where those living in Q4 and Q5 had significantly higher BMI than residents in Q1. There was no evidence of moderation of the relationship between neighbourhood socioeconomic disadvantage and BMI by park quantity as evidenced by the likelihood ratio test ($\chi^2(4) = 2.23$, $p = 0.682$). However, there was evidence of moderation by park quality ($\chi^2(4) = 11.22$, $p = 0.024$). As the number of facilities within each park increased, the differences in BMI between groups of neighbourhood socioeconomic disadvantage reduced between participants in Q3 ($\beta = 0.13$ (95%CI 0.21, 0.05)), compared to participants in Q1 (least disadvantaged). The interaction between park quality and neighbourhood disadvantage is shown in Fig. 1.

## 4. Discussion

This study examined the potential moderating effect of greenspace, considering both park quantity and quality, on the association between neighbourhood socioeconomic disadvantage and obesity. It is important to highlight that the quantity of park space in neighbourhoods did not moderate the relationship between neighbourhood socioeconomic disadvantage and BMI. However, the quality of park facilities, as indicated by the presence of diverse amenities, emerged as a crucial factor in this association. A significant observation was made regarding the relationship between an improvement in park quality and a reduction in the disparity of BMI among residents of neighbourhoods from various socioeconomic backgrounds: that is, as the number of park facilities increased, the differences in BMI between advantaged and disadvantaged neighbourhoods decreased. The observed impact was significant when examining individuals living in neighbourhoods with moderate levels of disadvantage (Q3) in comparison to those residing in areas with the least amount of disadvantage (Q1). This suggests that only the presence of greenspace is insufficient for reducing neighbourhood-level socioeconomic inequalities in obesity. Rather, the characteristics and resources present within these areas appear more important. While a significant association was observed in Q3, park quality appeared to have no impact in the most disadvantaged neighbourhoods (Q5). Similarly, Hobbs et al. (2017) found that although areas with moderate and the most disadvantage had better park quality than the least disadvantaged areas, they did not find an association with obesity. Notably, the study found that parks in the moderate and high disadvantaged areas experienced more incivilities (Hobbs et al., 2017). While the impact of

**Table 2**
Mean (sd) park quantity and park quality with 1.6 km buffer by neighbourhood disadvantage.

| Neighbourhood disadvantage | Park Quantity | Park Quality |
|---|---|---|
| **Q1 (least disadvantaged)** | 25.58 (11.35) | 7.18 (8.61) |
| **Q2** | 25.16 (15.32) | 7.01 (6.51) |
| **Q3** | 21.34 (10.16) | 7.04 (6.85) |
| **Q4** | 22.39 (9.31) | 6.30 (6.12) |
| **Q5 (most disadvantaged)** | 17.98 (10.64) | 6.19 (14.25) |

**Table 3**
Multilevel linear regression models of BMI by neighbourhood disadvantage, the quantity of parks within the neighbourhood and park quality.

| Neighbourhood disadvantage | Model 1: association between neighbourhood socioeconomic disadvantage and BMI[a] | Model 2: Interaction between neighbourhood disadvantage and park quantity[b] | Model 3: Interaction between neighbourhood disadvantage and park quality[c,d] |
|---|---|---|---|
| | β (95%CI) | β (95%CI) | β (95%CI) |
| **Q1 (least disadvantaged)** | Ref | Ref | Ref |
| **Q2** | 0.37 (−0.23, 0.97) | −0.03 (−0.07, 0.02) | −0.07 (−0.15, 0.01) |
| **Q3** | 0.47 (−0.15, 1.10) | −0.02 (−0.08, 0.04) | −0.13 (−0.21, −0.05) |
| **Q4** | 1.38 (0.68, 2.08) | 0.01 (−0.06, 0.08) | −0.09 (−0.20, −0.01) |
| **Q5 (most disadvantaged)** | 1.13 (0.40, 1.86) | −0.02 (−0.09, 0.04) | −0.05 (−0.11, 0.01) |

[a] Model 1: adjusted for gender, age, education, occupation, household income and neighbourhood self-selection.
[b] Model 2: Model 1 plus neighbourhood disadvantage * park quantity.
[c] Model 3: Model 1 plus neighbourhood disadvantage * park quality.
[d] represents the number of park facilities per percentage of greenspace within each participant's buffer i.e. for every additional park facility per one percent greenspace within the 1.6 km network buffer around each participant's residence.

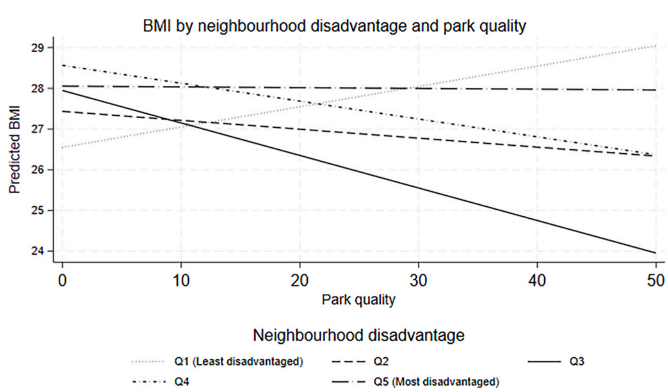


**Fig. 1.** Predicted BMI across levels of neighbourhood disadvantage and park quality score.

incivilities was not examined in our study, this may provide a possible explanation for the lack of association in Q5. Safety concerns or fear of crime may deter park usage (Bai et al., 2013).

The findings emphasise the significance of not only increasing greenspace, but also improving its quality, to successfully reduce socioeconomic disparities in obesity. This insight holds particular significance within the framework of public health strategies designed to address obesity (Kumanyika et al., 2010), particularly in nations such as Australia where obesity rates are rising (Australian Bureau of Statistics, 2023), and socioeconomic health inequalities are a significant concern (Rachele et al., 2017; Rachele et al., 2019; Anekwe et al., 2020). Public health interventions have the potential to address disparities in obesity rates among various socioeconomic groups by prioritising the enhancement of greenspaces in areas of disadvantage. This approach aims to foster a more equal health environment by emphasising the improvement of greenspace quality.

Our finding of neighbourhood-level inequalities in obesity aligns with Rachele et al. (2017, 2019) and Anekwe et al. (2020). The lack of moderating effect to park quantity on this association, in contrast to our finding of a moderating effect of park quality suggests that simply installing more greenspaces may not be sufficient to reduce area-level socioeconomic inequalities in obesity. However, the contrasting findings are not surprising. For example, findings by Blas-Miranda et al. (2022), suggested that the advantages of greenspace might have a more nuanced and context-specific influence from factors such as cultural, geographic, and socioeconomic distinctions. The lack of a significant moderating influence in our study for the quantity of park area on disparities in BMI among different socioeconomic groups challenges the assumption that increasing access to greenspaces always leads to improved obesity outcomes in the adult population. Forthcoming studies examining relationships between neighbourhood disadvantage, greenspace, and obesity, should include an examination of not only the presence of greenspace, but also its quality and the socio-cultural environment in which it is located.

In addition, the significance of the quality of greenspace, compared to its simple quantity, becomes clear when examining our results in relation to the study conducted by Rigolon et al. (2021). The authors conducted a systematic review on the potential of greenspace in moderating health disparities. However, our study indicates that the quality of park facilities may play a crucial role in addressing obesity disparities among adults, a factor that was not as strongly highlighted in their findings. In contrast, the research conducted by Putra et al. (2022) additionally indicates that the quality of greenspace, rather than simply their quantity (e.g., the level of greenness), might be a significant and more important measure of greenspace exposure. This is consistent with the results of the current study.

The findings of this study have several implications for policy and practice. According to the World Health Organization (WHO)'s plan to accelerate the fight against obesity at the 75th World Health Assembly in 2022, countries around the world are dedicating themselves to acting against obesity (World Health Organization, 2023a). Obesity as a global health challenge is linked to the Sustainable Development Goals (SDGs) in multiple ways. The SDGs do not specifically target obesity, but at least 14 of the 17 thematic SDG targets—including those for health, food, education, water quality, land and ocean quality, urbanisation, and employment—play a part in fuelling the obesity epidemic (Lobstein and Cooper, 2020). Furthermore, the research on neighbourhood socioeconomic inequalities in obesity is closley aligned with SDG 11—"Sustainable Cities and Communities". This alignment comes from the recognition that physical activity plays a crucial role in promoting good health and preventing and managing obesity (Lobstein and Cooper, 2020). The achievement of these objectives can be facilitated by focusing on targets such as promoting active travel (11.2) and promoting access to urban greenspaces (11.7) (Lobstein and Cooper, 2020). The findings of the current study suggest that improving the quality of greenspace can support the development of a health-promoting urban environments (SDG 11) and contribute to the prevention of obesity (SDG 3), as well as reducing inequalities (SDG 3, 4, 5. and 10).

### *4.1. Study strengths and limitations*

This study has several strengths and limitations. One of the primary strengths of this study lies in its representativeness. By making use of data from the HABITAT project, the study emphasises a broad and diverse sample, which includes a wide range of socioeconomic backgrounds and urban environments. The presence of diversity within our study population contributes to the broader relevance of our research findings to similar urban populations, though generalisability may be limited to mid-to-older aged adults.

Furthermore, conducting a comprehensive examination of the park quality, including a diverse range of amenities, rather than simply quantity, offers a more comprehensive understanding of the ways in which greenspaces can impact obesity prevalence within different socioeconomic settings. Last, in this study we were able to account for residential self-selection effects. A lack of adjustment for residential self-selection is problematic when examining associations between neighbourhood characteristics and health behaviours and outcomes due to the risk of confounding: when residents choose where they live, they may select their neighbourhood according to their lifestyle and personal preferences (McCormack and Shiell, 2011; Van Dyck et al., 2011).

This study has several limitations. First, the cross-sectional design limits our capacity for determining a causal relationship. Although there are observable connections between park quality, the socioeconomic status of neighbourhoods, and the prevalence of obesity, it remains challenging to truly determine the causal direction of these relationships. However, the reverse association, e.g., obesity causing neighbourhood disadvantage and greenspace, would appear less plausible. Second, attrition in HABITAT was higher among participants from lower socioeconomic backgrounds, meaning that those participants have less representation in this study, which used the fifth wave. In addition, using self-reported data for calculating BMI may potentially lead to reporting bias (Bauhoff, 2014), although this is a common challenge in large-scale epidemiological studies. Furthermore, BMI fails to distinguish between fat and muscle mass, and does not consider visceral fat, a key factor in the metabolic effects of obesity (Gurunathan and Myles, 2016). Last, the study's focus on a specific urban Australian background may limit the applicability of its findings to rural or non-Australian settings, suggesting a need for caution in applying these results too broadly.

### 4.2. Future research priorities

Based on the limitations identified in our study, it is evident that there are several areas that need further investigation. An important area for future research would involve the implementation of a longitudinal design. This approach could assist researchers in monitoring trends over time, thereby providing valuable insights into the causal connections between neighbourhood attributes, the quality of greenspace, and obesity. Longitudinal studies also provide the opportunity to examine temporality: how changes in neighbourhood disadvantage and greenspace are associated with changes in BMI. This temporality, while also adjusting for selection effects, provides a stronger basis to infer causation. Considering that evidence of moderation by park quality was only observed in Q3 and not the Q4 or Q5, future research should aim to understand the potential reasons for the lack of association in the most disadvantaged neighbourhoods. To further elucidate the complex relationship between neighbourhood disadvantage and BMI, future research should also consider other potential moderators not included in this study (e.g., occupation type, age, mode of travel).

Furthermore, it is recommended that future studies consider the inclusion of objective measures of BMI, such as clinical assessments, to reduce the potential biases that may result from self-reported data. Including rural and other diverse settings into the research focus could bring significant value, as it would provide a more comprehensive understanding of the interplay between greenspace and socioeconomic factors across multiple environments.

Finally, given the specific findings regarding park quality, further exploration into specific attributes of greenspace that most effectively contribute to reducing obesity disparities would be beneficial. This research has the potential to provide valuable insights for the development of specific public health interventions and urban planning strategies, which in response might lead to the promotion of equitable health outcomes among diverse socioeconomic groups.

This study examined the complex association between socioeconomic disadvantage at the neighbourhood level, greenspace, and obesity. Specifically, the research focused on examining how the quality and quantity of parks may moderate the relationship between neighbourhood disadvantage and obesity. The results highlight the complex nature of this association, particularly within the demographic of mid-to-older- aged adults. Although the impact of greenspace quantity, as indicated by the quantity of park area, on the relationship between neighbourhood socioeconomic disadvantage and BMI was not found to be statistically significant, the quality of parks emerged as a crucial moderating factor. This study emphasises the significance of quality greenspace in addressing socioeconomic disparities in obesity.

In conclusion, this study makes an important contribution to the increasing amount of research regarding the impact of greenspace on public health, with a specific focus on its relationship to obesity and socioeconomic inequalities. It underscores the need for nuanced public health strategies and urban planning that prioritise the quality of greenspace to promote healthier, more equitable communities. The present study not only corresponds with global health targets, as delineated by the WHO and SDGs, but also offers practical insights for policymakers and urban planners to address the issue of obesity and reduce health inequalities among socioeconomically diverse communities.

## Conflicts of interest

None declared.

## CRediT authorship contribution statement

**Beiou Zhang:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Venurs Loh:** Writing – review & editing, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Rebecca A. Reid:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Tafadzwa Nyanhanda:** Writing – review & editing, Project administration. **Tara Jamalishahni:** Writing – review & editing, Data curation. **Gavin Turrell:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Jerome N. Rachele:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

## Data availability

Data will be made available on request.

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